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CO_2 emissions, economic and population growth, and renewable energy: Empirical evidence across regions

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ABSTRACT

This study empirically investigates the nexus among carbon dioxide (CO_2) emissions, economic and population growth, and renewable energy across regions. To do so, an unbalanced panel dataset of 128 countries over the period 1990–2014 is utilized. Considering the cross-sectional dependence and slope homogeneity observed in the panel, a series of econometric techniques allowing for cross-sectional dependence and slope homogeneity is employed. The results of cross-sectional dependence and slope homogeneity tests confirm the existence of significant cross-sectional dependence and heterogeneity. The empirical results of the common correlated effects mean group (CCEMG) estimator indicate that, at both the global and regional levels, population size and economic growth positively and significantly influence CO_2 emission levels. Furthermore, although increased renewable energy intensity leads to a decline in CO_2 emissions for all of the six regions, its coefficient in S. & Cent. America and Europe & Eurasia is considerably higher than the levels seen in other regions, which may be affected by the proportion of renewable energy in the primary energy mix. Finally, the results of panel causality testing provide evidence of varied causality links among the variables across regions.

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1. Introduction

In the last few decades, the world has witnessed unparalleled economic development thanks to rapid industrialization and urbanization. According to the World Bank (2017), the gross domestic product (GDP) has increased dramatically, by approximately twofold, from $37,224.4 billion US (constant 2010 US$) in 1990 to $72,247.0 billion US in 2014, with an average annual growth rate of 2.7% (Fig. 1). Simultaneously, the global population size has risen rapidly (approximately 1.5 times) from 5.3 billion in 1990 to 7.3 billion in 2014, with an average annual growth rate of 1.3% (World Bank, 2017). One of the consequences of such economic and population growth is rapidly increasing energy consumption across the globe. Based on statistics from BP (formerly British Petroleum) (BP, 2017), global energy consumption has increased by approximately two times, from 8133.3 million tonnes oil equivalent (Mtoe) in 1990 to 12,928.4 Mtoe in 2014 (Fig. 1). The rapidly increasing energy demand, however, has posed tremendous environmental challenges, particularly the global climate change caused by the increased concentration of carbon dioxide (CO_2) emissions mainly emitted from fossil fuel burning (Jardón et al., 2017; Tol, 2002a, 2002b, 2005, 2009). Fossil fuel-based global CO_2 emissions have increased by around two times from 22.7 billion tons in 1990 to 35.5 billion tons in 2014 (Fig. 1). Increasing CO_2 emissions and the associated global climate change have ignited worldwide concerns, evidenced from the establishment of important international organizations such as the United Nations Framework Convention on Climate Change (UNFCCC) and the

Abbreviations: ADF, Augmented Dickey Fuller; AMG, Augmented mean group; BP, British Petroleum; BRICS, Brazil, Russia, India, China, and South Africa; CADF, Cross-sectionally ADF; CCEMG, Common correlated effects mean group; CD, Cross-section dependence; CIPS, Cross-sectionally augmented Im, Pesaran, and Shin; CO_2, Carbon dioxide; D-H, Dumitrescu-Hurlin; DOLS, Dynamic OLS; EIA, US Energy Information Administration; Europe & Eurasia, Europe and Eurasia; EU, European Union; FMOLS, Fully modified OLS; GDP, Gross domestic product; GMM, General method of moments; IEA, International Energy Agency; IPS, Im, Pesaran, and Shin; LLC, Levin-Lin-Chu; LM, Lagrange multiplier; Mtoe, Million tonnes oil equivalent; OECD, Organization for Economic Cooperation and Development; OLS, Ordinary least squares; PMG, Pooled mean group; PP, Phillips-Perron; PS, Population size; REI, Renewable energy intensity; RMSE, Root mean square error; SAARC, South Asian Association for Regional Cooperation; S. & Cent. America, South and Central America; STIRPAT, Stochastic Impacts by Regression on Population, Affluence, and Technology; UNFCCC, United Nations Framework Convention on Climate Change; US, United States; VECM, Vector error correction model; WDI, World Development Indicators.

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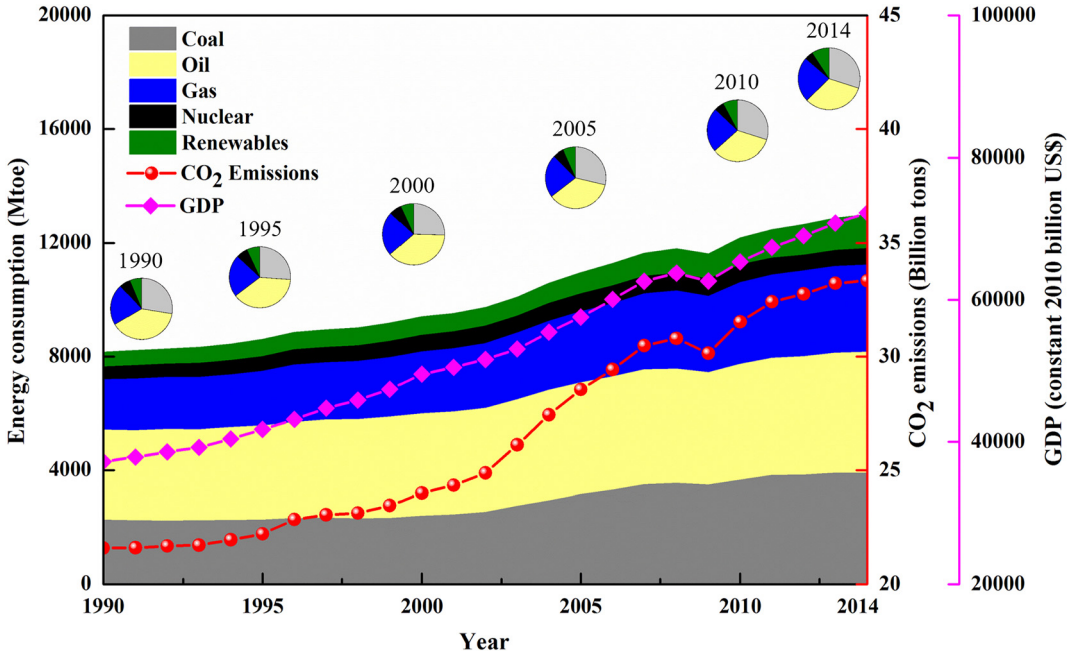

Fig. 1. Global CO_2 emissions, economic growth, and primary energy mix from 1990 through 2014. (*Data source*: BP, 2017; World Bank, 2017.)

opening of international climate change conferences such as the 2015 Paris Climate Change Conference.

According to Bilgili et al. (2016), Dong et al. (2017a), and Goh and Ang (2018), renewable energy is optimal for a cleaner energy consumption structure through the substitution away from fossil fuels and, therefore, leads to less CO_2 emission. Therefore, as a way to deal with global warming, renewable energy has emerged as an effective alternative to fossil fuels and a widely accepted pathway toward sustainable growth (Bhattacharya et al., 2017). The world has huge demand for renewable energies, including hydropower, solar, wind, geothermal, and biomass (Dong et al., 2017b). As shown in Fig. 1, global renewable energy consumption has increased by more than two times, from 514.7 Mtoe in 1990 to 1196.6 Mtoe in 2014, and is expected to increase to 4662.0 Mtoe in 2040, according to the forecast results under the 450 Scenario of the International Energy Agency's (IEA's) World Energy Outlook 2016 (IEA, 2017).

Given the above background, a better understanding of the nexus among CO_2 emissions, economic and population growth, and renewable energy is particularly useful for policymakers and government officials - not only in devising long- and short-run policies for tackling CO_2 emissions, but also in promoting growth in the renewable energy industry. Although the emission-growth-renewables nexus has been extensively studied at a single-country and regional levels, very few studies have been conducted at the global level (see the second column in Table A1 in Appendix A). Also, another fact that cannot be ignored is that there are significant differences in CO_2 emissions, population size, economic growth, and renewable energy consumption across the globe (Hoogwijk et al., 2004; Raupach et al., 2007; also see Fig. 2a–d). However, to the best of our knowledge, most cross-national studies on the emission-growth-renewables nexus ignore the differences in various subgroups of regions. In addition, as seen in the last column in Table A1, the cross-sectional dependence and slope homogeneity that may exist within cross countries are frequently ignored in prior cross-national studies on the emission-growth-renewables nexus, which can create inconsistent estimates or even result in misleading conclusions (Breitung, 2005; Grossman and Krueger, 1995).

To fill this knowledge gap and contribute to the emerging literature, this study aims to examine the nexus among CO_2 emissions, economic and population growth, and renewable energy for a broad sample of 128 countries for 1990–2014 with consideration of the differences in geographic location of the various regions. Considering the cross-sectional dependence and slope homogeneity observed in the global panel and subpanels, a causality framework covering panel unit root, cointegration, estimation, and causality tests allowing for cross-sectional dependence and slope homogeneity is employed in this study.

Two main features distinguish this study from previous studies on the research topic and contribute to filling the gap in the literature. First, considering the differences in various subgroups of regions, 128 countries are divided into six regions in this study and, thus, the driving factors of CO_2 emissions across various regions are identified. This is particularly useful for global and/or regional policymakers and government officials in devising specific and effective policies to mitigate CO_2 emissions. Second, different from the widely employed first-generation estimators that ignore cross-sectional dependence and slope homogeneity, the estimation techniques in this study, which allow for cross-sectional dependence and slope homogeneity, can provide a more robust analysis of the causal links between all the selected variables.

The remainder of this study is structured as follows. Section 2 provides an overview of the related literature. Section 3 discusses the model, estimation techniques, and data. Section 4 presents the empirical results. Section 5 contains further discussion. Section 6 presents the major findings and provides policy implications.

2. Literature review

2.1. Existing research on the emission, growth, and renewables nexus

With rapidly increasing consumption of renewable energy, a growing body of researchers has investigated the role of renewable energy consumption in affecting CO_2 emissions at the country-specific level, regional level, and global level (see Table A1). For example, at the country-specific level, using Toda-Yamamoto causality tests to investigate Italy's case, Bento and Moutinho (2016) report long-term, unidirectional causality running from per capita renewable electricity

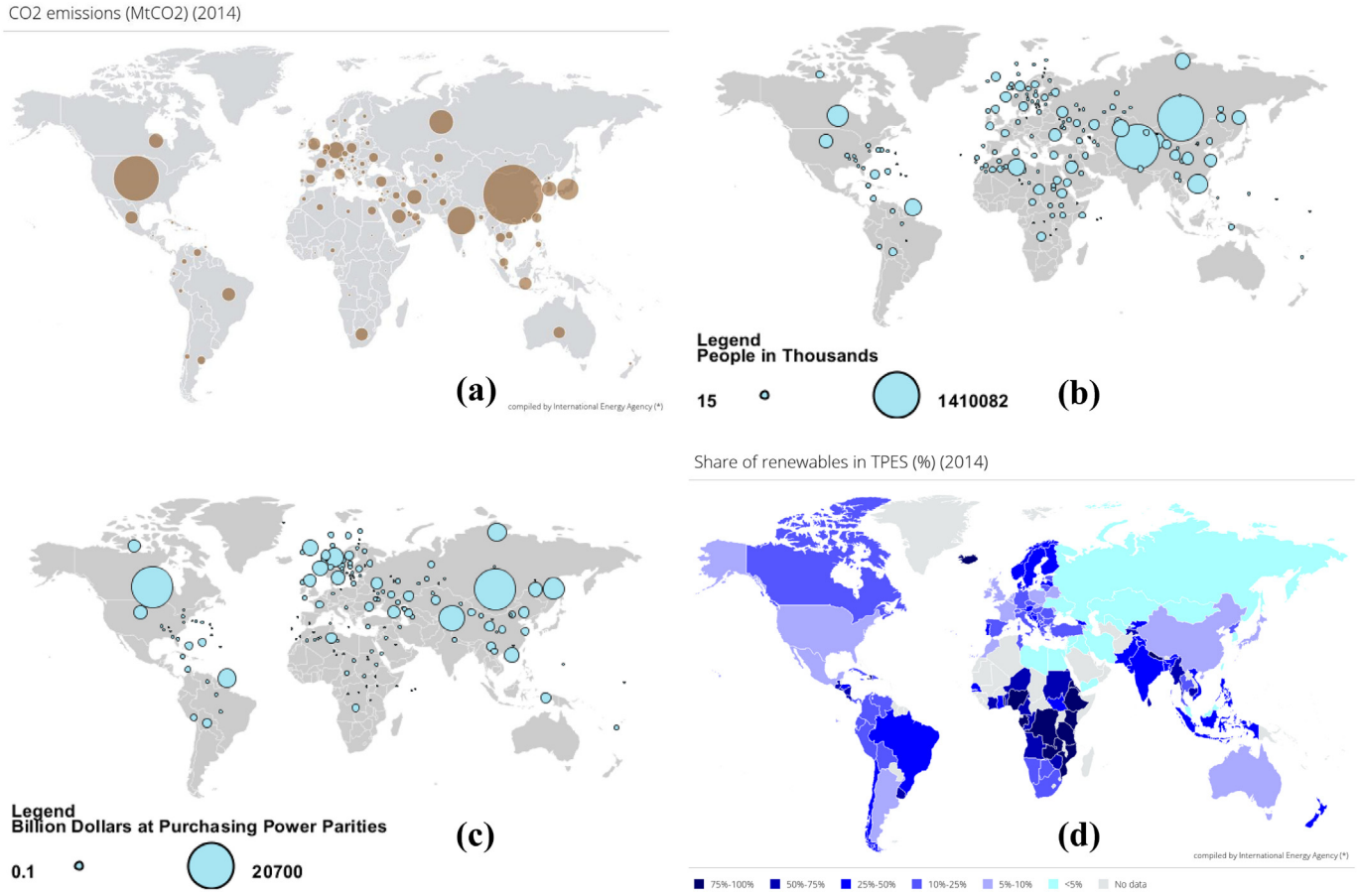

Fig. 2. Spatial characteristics of (a) total CO_2 emissions (million ton, Mt), (b) population (thousands), (c) GDP (billion dollars), and (d) share of renewable energy in total primary energy supply (%) in 2014 across the globe.
(*Data sources*: panels a and d are from the IEA Atlas of Energy (IEA, 2018), while panels b and c are from the International Energy Statistics published in the US Energy Information Administration (EIA, 2018).)

production to CO_2 emissions. In the case of Algeria, Bélaïd and Youssef (2017) employ the vector error correction model (VECM) Granger causality technique and suggest that, in the long run, renewable energy use has a beneficial environmental effect. Using the same Granger causality technique, Danish et al. (2017) discover that bi-directional causality exists between renewable energy consumption and CO_2 emissions. For the case of China, Dong et al. (2018a, 2018c) explore the effect of renewable energy consumption on CO_2 emissions and conclude that increasing renewable energy consumption can lead to less CO_2 emission.

At the regional level, based on the Dumitrescu–Hurlin panel Granger causality test, Dogan and Seker (2016) identify a bidirectional causal relationship between CO_2 emissions and renewable energy for the European Union (EU). With respect to a panel of 25 Organization for Economic Cooperation and Development (OECD) countries, VECM panel Granger causality results from Jebli et al. (2016) indicate bidirectional causality running between CO_2 emissions and renewable energy. The VECM panel Granger causality approach Dong et al. (2017a) employ indicates that renewable energy consumption substantially reduces CO_2 emissions for a panel of BRICS countries (i.e., Brazil, Russia, India, China, and South Africa).

However, to the best of our knowledge, very few studies have examined the role of renewable energy in CO_2 emissions at the global level. For instance, results obtained by Bhattacharya et al. (2017) from system general method of moments (GMM) and fully modified ordinary least squares (FMOLS) reveal that the growth of renewable energy consumption has a significant negative impact on CO_2 emissions for a panel of 85 developed and developing economies across the globe. Furthermore, as mentioned in the previous section (i.e., section 1), the world exhibits significant differences in CO_2 emissions and renewable energy consumption. It would, therefore, be interesting to examine how renewable energy affecting CO_2 emissions differs across regions. However, based on a review of the literature to date, most cross-national studies on the emission, growth, and renewables nexus overlook the differences in various subgroups of regions.

2.2. Existing research on panel estimation approaches

In general, the estimation methods used for panel analysis can be divided into two categories: first-generation estimators and second-generation estimators. Of the first-generation estimators, the most commonly used estimators include GMM estimator, FMOLS estimator, and dynamic OLS (DOLS) estimator. For example, many studies have used the GMM estimator to analyze the effect of renewable energy consumption on CO_2 emissions, such as Shafiei and Salim (2014) for OECD countries, Ito (2017) for 42 developing countries, Zoundi (2017) for 25 African countries, and Bhattacharya et al. (2017) for 85 developed and developing economies across the world. On the other hand, FMOLS and DOLS estimators are also usually used to investigate the relationship between CO_2 emissions and renewable energy consumption, such as Apergis and Payne (2014) for seven Central American countries, Zeb et al. (2014) for selected South Asian Association for Regional Cooperation (SAARC) countries, Bilgili et al. (2016) for 17 OECD countries, Dogan and Seker (2016) for 15 EU countries, Dong et al. (2017c) for 30 of China's provinces, and Liu et al. (2017) for a panel of BRICS countries. Although the above first-generation estimators are both relatively simple and clear and able to examine how renewable energy

affects CO_2 emissions, they are not robust to the cross-sectional dependence and slope homogeneity that may exist within cross countries (Dong et al., 2018b, 2018d), which can create inconsistent estimates or even result in misleading conclusions (Breitung, 2005; Grossman and Krueger, 1995).

Considering the limitations of the first-generation estimators, some second-generation estimators have been developed in recent years, principally including the augmented mean group (AMG) estimator developed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010), the common correlated effects mean group (CCEMG) estimator introduced by Pesaran (2006) and advanced by Kapetanios et al. (2011), and the pooled mean group (PMG) estimator of Pesaran et al. (1996). However, to the best of our knowledge, only a few studies have used the second-generation estimators (e.g., AMG and CCEMG) to analyze the emission-growth-renewables nexus; see Sebri and Ben-Salha (2014) and Dong et al. (2017a) for BRICS countries, Özbuğday and Erbas (2015) for 36 selected countries, and Ito (2017) for a panel of 42 developed countries.

3. Model, methodology, and data

3.1. Empirical model

The stochastic impacts by regression on population, affluence, and technology (STIRPAT) model, developed by Dietz and Rosa (1997), suggests that population and economic activity are important sources of CO_2 emissions. In addition to these two driving forces, we assume that availability of renewable energy leads to a reduction in CO_2 emissions. To effectively capture these changes in the availability of renewable energy while holding population and economic activity constant, renewable energy is measured by renewable energy intensity. Therefore, the multivariate framework is as follows:

$$CO_{2it} = f(PS_{it}, GDP_{it}, RE_{it}) \tag{1}$$

To reduce the risk of heteroskedasticity, after taking natural logarithms, the model can be represented as follows:

$$\ln(CO_{2it}) = \beta_0 + \beta_1 \ln(PS_{it})_t + \beta_2(GDP_{it}) + \beta_3 \ln(REI_{it}) + \mu_{it} \tag{2}$$

where subscripts i and t denote country and year, respectively; $\beta_1 - \beta_3$ are the parameters to be estimated; CO_2 represents the amount of CO_2 emissions; *PS* indicates population size; *GDP* describes per capita GDP; *REI* denotes renewable energy intensity, which is measured in renewable energy use per capita GDP by referring to the works of López-Menéndez et al. (2014) and Yang (2014); β_0 is a constant term; and μ is a random error term.

3.2. Estimation techniques

The estimation procedure used here consists of six key steps: (1) Two tests, the Pesaran scaled Lagrange multiplier (LM) test and Pesaran cross-section dependence (CD) test, are utilized to test for cross-sectional dependence (Section 3.2.1); (2) the slope homogeneity test introduced by Pesaran and Yamagata (2008) is conducted (Section 3.2.2); (3) to test the stationarity of each variable, the Pesaran cross-sectionally augmented Im, Pesaran, and Shin (Pesaran CIPS) panel unit root test is utilized (Section 3.2.3); (4) to examine the cointegrating relationship between all the selected variables, the Westerlund panel cointegration test is conducted (Section 3.2.4); (5) the long-run parameters of independent variables are estimated by employing two estimator techniques: the panel FMOLS estimator and CCEMG estimator, and the important factors of CO_2 emissions in different regions are identified (Section 3.2.5); and (6) the empirical direction of the causal relationship is confirmed by the Dumitrescu-Hurlin (D-H) panel causality approach (Section 3.2.6).

3.2.1. Cross-sectional dependence test

Cross-sectional dependence is an important issue in panel data econometrics and ignoring cross-sectional dependence would likely create inconsistent estimates and lead to misleading information (Grossman and Krueger, 1995). Therefore, before analyzing stationarity properties of all variables, this study first tests for cross-sectional dependence by using the Pesaran scaled LM test and the Pesaran CD test proposed by Pesaran (2004).

The Breusch-Pagan LM test is valid for small N and T (Breusch and Pagan, 1980) and can be calculated as follows:

$$LM_1 = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \rightarrow \chi^2 \frac{N(N-1)}{2} \tag{3}$$

Since the Breusch-Pagan LM test is not appropriate for large N, Pesaran proposes a standardized version of the LM statistic, the Pesaran scaled LM test. This test is appropriate for large N and T and can be calculated as follows:

$$LM_2 = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T_{ij}\hat{\rho}_{ij}^2 - 1\right) \rightarrow N(0,1) \tag{4}$$

To address the size distortion of the Breusch-Pagan LM test and the Pesaran scaled LM test, Pesaran proposes an alternative statistic, the Pesaran CD test; this statistic is valid for large N and fixed T and can be expressed as follows:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \rightarrow N(0,1) \tag{5}$$

In these statistics, $\hat{\rho}_{ij}$ indicates the correlation coefficients obtained from the residuals of the model as described above. The model as described above is asymptotically distributed as standard normal if the null hypothesis considers $T_{ij} \rightarrow \infty$ and $N \rightarrow \infty$ as well.

3.2.2. Slope homogeneity test

As Breitung (2005) reports, assuming slope homogeneity will result in misleading estimates if the panel is heterogeneous. Thus, cross-sectional heterogeneity should be controlled when investigating the empirical results. Swamy (1970) proposes the homoskedasticity assumption framework to test the slope homogeneity assumption when N is fixed relative to T. Since the data used here have a fairly large N and T, this study employs the slope homogeneity test developed by Pesaran and Yamagata (2008) because it is valid in panels with large N and T. The test statistics used in the slope homogeneity test of Pesaran and Yamagata are as follows:

$$S = \sum_{i=1}^{N} (\beta_i - \beta_{WFE})' \frac{x_i' M_\tau x_i}{\sigma_i^2} (\beta_i - \beta_{WFE}) \tag{6}$$

$$\Delta = \sqrt{N}\left(\frac{N^{-1}S - k}{\sqrt{2k}}\right) \tag{7}$$

where S and Δ are the test statistics, β_i is the pooled ordinary least squares (OLS) coefficient, β_{WFE} is the weighted fixed effect pooled estimator, x_i is the matrix containing explanatory variables in deviations from the mean, M_τ is the identity matrix, σ_i^2 is the estimate of σ_i, and k is the

number of regressors. The biased-adjusted version of the Δ test is denoted below:

$$\Delta_{adj} = \sqrt{N}\left(\frac{N^{-1}S - k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right) \tag{8}$$

3.2.3. Panel unit root test

Since there is cross-sectional dependence across countries in the panel, first-generation conventional panel unit root tests (e.g., Levin-Lin-Chu (LLC), Im, Pesaran, and Shin (IPS), augmented Dickey-Fuller (Fisher-ADF), and Phillips-Perron (Fisher-PP) panel unit root tests) which do not allow cross-sectional dependence in data are not valid. To address this shortcoming, Pesaran (2007) proposes a new second-generation panel unit root test allowing for cross-sectional dependence, the Pesaran CIPS panel unit root test. Unlike other panel unit root tests, to asymptotically eliminate the cross-sectional dependence, Pesaran augments the ADF regressions with the cross-section averages of lagged levels and first differences for each unit, which is denoted as cross-sectionally augmented Dickey-Fuller (CADF). This statistic can be calculated as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \overline{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + e_{it} \tag{9}$$

where $\overline{y}_{t-j}$ and $\Delta\overline{y}_{t-j}$ are the cross-sectional averages of lagged levels and first differences of individual series, respectively. After running the CADF statistics, the CIPS statistic can be estimated as follows:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i \tag{10}$$

where $CADF_i$ is the t-statistics in the CADF regression defined by Eq. (9).

3.2.4. Panel cointegration test

The common cointegration tests (e.g., the Pedroni panel cointegration test developed by Pedroni (2001)) might provide biased results since they ignore cross-sectional dependence. Since the data used here are cross-sectionally dependent, this study employs the error correction-based panel cointegration tests advanced by Westerlund (2005) to explore the cointegration relationship between all selected variables, which can be estimated as follows:

$$\Delta z_{it} = \delta_i' d_i + \theta_i \left(z_{i(t-1)} + \pi_i' y_{i(t-1)}\right) + \sum_{j=1}^{m} \theta_{ij} \Delta z_{i(t-j)} + \sum_{j=0}^{m} \varphi_{ij} \Delta y_{i(t-j)} + \omega_{it} \tag{11}$$

where θ_i is the adjustment term which determines the speed by which the system adjusts back to the equilibrium relationship. Accordingly, based on least squares estimates of θ_i, the statistics of Westerlund error correction-based panel cointegration tests can be calculated:

$$G_\tau = N^{-1} \sum_{i=1}^{N} \frac{\theta_i}{SE\left(\hat{\theta}_i\right)} \tag{12}$$

$$G_\alpha = N^{-1} \sum_{i=1}^{N} \frac{T\theta_i}{\theta_i'(1)} \tag{13}$$

where G_τ and G_α are called group mean statistics, and rejection of the null hypothesis implies the presence of cointegration for at least one cross-sectional unit in the panel (Shahbaz et al., 2017):

$$P_\tau = \frac{\hat{\theta}_i}{SE\left(\hat{\theta}_i\right)} \tag{14}$$

$$P_\alpha = T\hat{\theta}_i \tag{15}$$

where P_τ and P_α are called panel statistics, and rejection of the null hypothesis indicates rejection of no cointegration for the panel as a whole.

3.2.5. Panel long-run estimates

After the presence of a cointegration relationship is confirmed, this study first employs the panel FMOLS model to calculate the long-run elasticity values for the full panel and for each subpanel. The panel FMOLS model is developed by Pedroni (2001), which can be written as:

$$\hat{\beta}_{FMOLS} = N^{-1} \sum_{i}^{N} \hat{\beta}_{FMOLS,n} \tag{16}$$

where $\hat{\beta}_{FMOLS,n}$ represents the FMOLS estimator applied to country *i*. The associated t-statistic can be obtained as follows:

$$t_{\hat{\beta}_{FMOLS}} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}_{FMOLS,n}} \tag{17}$$

However, as a traditional estimator, the FMOLS estimator does not take cross-sectional dependence and slope homogeneity into account, which would produce inconsistent estimates (Pesaran and Smith, 1995). Thus, this study also uses the CCEMG estimator that allows for cross-sectional dependence and slope homogeneity and further investigates the effect of cross-sectional dependence and slope homogeneity on the long-run elasticity values by comparing these two estimates. The CCEMG estimator is first introduced by Pesaran (2006) and then advanced by Kapetanios et al. (2011); it is robust to cross-sectional dependence and slope homogeneity. In this estimator, the linear combinations of the cross-sectional averages of the observed common effects as well as the variables are utilized (Atasoy, 2017; Kapetanios et al., 2011). The CCEMG estimator can be estimated as follows:

$$y_{it} = a_{1i} + b_i x_{it} + c_i f_t + \alpha_i \overline{y}_{it} + \beta_i \overline{x}_{it} + e_{it} \tag{18}$$

where y_{it} and x_{it} are observables; b_i is the country-specific estimates of coefficients; f_t is the unobserved common factor with heterogeneous factor; a_i and e_{it} are the intercept and error term, respectively.

3.2.6. Panel causality test

Testing for causality direction is the most important step when examining the macroeconomic relationships, which is particularly useful for policymakers in developing specific policies. Therefore, to examine this issue of causality, the D-H panel causality test, which allows for cross-sectional dependence, is employed in this empirical study. The D-H panel causality test is proposed by Dumitrescu and Hurlin (2012) based on the individual Wald statistic of Granger (1969) non-causality averaged across the cross-section units. The linear panel regression model of the D-H panel causality test is as follows:

$$y_{it} = a_i + \sum_{j=1}^{J} \lambda_i^j y_{i(t-j)} + \sum_{j=1}^{J} \beta_i^j x_{i(t-j)} + e_{it} \tag{19}$$

where *y* and *x* are observables, and the autoregressive parameters λ_i^j and regression coefficient estimates β_i^j are assumed to vary across cross-sections.

As Dumitrescu and Hurlin (2012) point out, the null of no causal relationship for any of the subgroups ($H_0 : \beta_i = 0 \quad i = 1, 2, \cdots, N$) and the alternative hypothesis that causal relationships occur for at least one subgroup of the panel ($H_1 : \beta_i = 0 \quad i = 1, 2, \cdots, N_1; \beta_i \neq 0 \quad i = N_1 + 1, N_1 + 2, \cdots N$) in the D-H panel causality test can be tested based on an average Wald statistic. Therefore, the average of the individual Wald statistic generated by the D-H panel causality test can be represented as follows:

$$W_{N,T}^{HNC} = N^{-1} \sum_{i=1}^{N} W_{i,T} \tag{20}$$

where $W_{i,T}$ is the individual Wald statistic for each cross-section unit.

3.3. Data and descriptive statistics

To investigate the emission-growth-renewables nexus across the globe, this study uses a panel dataset for a panel of 128 countries covering 1990–2014, yielding a total of 3200 observations. To fully address the concern about whether the effect of renewable energy on CO_2 emissions differs across regions, the 128 countries are classified into six groups based on their locations and the regional division method used in the BP statistical review of world energy (BP, 2017): North America, South and Central America (S. & Cent. America), Europe and Eurasia (Europe & Eurasia), Middle East, Africa, and Asia Pacific. The North America subpanel in this study consists of data for three countries, while the S. & Cent. America, Europe & Eurasia, Middle East, Africa, and Asia Pacific subpanels comprise data for 22 countries, 40 countries, 14 countries, 25 countries, and 24 countries, respectively (see Table A3).

The data on CO_2 emissions (CO_2, measured in metric tons), population size (*PS*, measured in number), per capita GDP (*GDP*, measured in constant 2010 US$), and renewable energy intensity (*REI*, measured in kg of oil equivalent per constant 2010 US$) are obtained from the World Development Indicators (WDI) published by the World Bank (2017). Notably, the sample is unbalanced as the data on some variables are missing for a number of countries in the WDI. Detailed descriptions of the variables and the data sources used in this study are also listed in Table A2. Table 1 presents the summary statistics of all four variables for the six subpanels and also for the whole sample.

Table 1
Descriptive statistics of the variables (after logarithm).

Panel	Statistics	lnCO_2	ln*PS*	ln*GDP*	ln*REI*
North America	Mean	20.7618	18.3977	10.1346	−3.9159
	Std. Dev.	1.1749	0.9123	0.7873	0.6051
	Maximum	22.4794	19.5793	10.8353	−3.0517
	Minimum	19.5789	17.1402	8.8899	−4.8122
	Observations	75	75	75	75
S. & Cent. America	Mean	17.0660	16.4909	8.4219	−2.9376
	Std. Dev.	1.9844	1.6622	0.7366	0.9595
	Maximum	21.3717	20.2522	9.7440	−0.7529
	Minimum	12.6139	14.0159	6.4957	−6.0294
	Observations	550	550	543	503
Europe & Eurasia	Mean	17.6908	15.8742	9.6598	−4.0638
	Std. Dev.	1.6489	1.5162	1.1140	1.3163
	Maximum	21.5533	19.1347	11.6260	−0.9665
	Minimum	14.2498	12.4483	6.7868	−9.3550
	Observations	1000	1000	972	960
Middle East	Mean	18.6513	17.5465	8.3291	−4.2186
	Std. Dev.	2.1292	2.2308	1.2823	3.0949
	Maximum	23.7791	22.5304	11.1215	1.4800
	Minimum	14.4474	14.4362	5.9011	−10.8463
	Observations	350	350	350	344
Africa	Mean	15.5426	16.2197	7.3073	−1.7825
	Std. Dev.	1.2278	1.3771	1.0130	1.6246
	Maximum	18.7950	18.9886	9.3865	1.0333
	Minimum	10.6050	12.9177	5.0866	−8.5460
	Observations	625	625	625	612
Asia Pacific	Mean	18.0806	17.3276	8.0442	−3.2917
	Std. Dev.	1.9224	1.6516	1.5493	2.2170
	Maximum	23.0546	21.0339	10.9040	0.1921
	Minimum	13.3604	14.5967	5.2640	−11.0116
	Observations	600	600	597	593
Global panel	Mean	17.4139	16.5622	8.5412	−3.2934
	Std. Dev.	2.0688	1.7611	1.4579	1.9975
	Maximum	23.7791	22.5304	11.6260	1.4800
	Minimum	10.6050	12.4483	5.0866	−11.0116
	Observations	3200	3200	3162	3087

Note: Std. Dev. denotes standard deviation.

4. Empirical results

4.1. Results of cross-sectional dependence and slope homogeneity tests

The results of cross-sectional dependence and slope homogeneity tests are presented in Table 2. For the global panel, the null hypothesis of no cross-sectional independence is rejected at the 1% level of significance, indicating strong cross-sectional dependence. This study further finds that the null hypothesis for the six subpanel countries is rejected at the 1% or 5% level, implying that methods allowing for cross-sectional dependence are more appropriate in this study. Table 2 also provides the results from the two slope homogeneity tests (i.e., Δ and Δ_{adj}). Both tests reject the null hypothesis of the slope homogeneity hypothesis for the global panel and six subpanel countries, confirming the presence of heterogeneity. Consequently, in addition to cross-sectional dependence, the methods used in this study should also be robust to slope homogeneity.

4.2. Results of panel unit root test

To examine the stationarity and determine the integration level of all selected variables, this study employs the Pesaran CIPS panel unit root test; the test results are displayed in Table 3. It is clear that, for the global panel and six subpanel countries, not all variables are stationary at levels. When the first difference is taken, the null hypothesis of the unit root is rejected for all the variables, implying that all the variables in this study are integrated on the order of one, that is, I (1). Accordingly, the unique order of integration of all the variables allows us to examine whether a long-run equilibrium relationship exists among the selected variables by employing the error correction-based panel cointegration tests advanced by Westerlund.

4.3. Results of panel cointegration test

The results of the Westerlund panel cointegration test for the global panel and six subpanel countries are illustrated in Table 4; the long-run cointegrating relationship is supported by all Westerlund test statistics when considering the global panel. For the six subpanel countries, the hypothesis of cointegration is also supported by the Westerlund test statistics, indicating the existence of a long-run equilibrium relationship between CO_2 emission and its determinants within the global panel and six subpanel countries over 1990–2014. The existence of a panel cointegration relationship among all four variables serves the basic purpose of this study and enables us to further investigate the effects of population growth, GDP, and renewable energy on CO_2 emissions.

4.4. Estimation results

After implementing cross-sectional dependence, slope homogeneity, unit root, and cointegration tests, the next step is to calculate the long-run estimates for the global panel and various regions. The results of the panel FMOLS and CCEMG estimators for the global panel of 128 countries and various regions are shown in Table 5. From this table, these two estimation methodologies provide dissimilar results. Based on the results of the panel FMOLS estimator, the coefficients of some

Table 2
Cross-sectional dependence and slope homogeneity analysis.

Region	Cross-sectional dependence test			Slope homogeneity test	
	Breusch-Pagan LM	Pesaran scaled LM	Pesaran CD	Δ	Δ_{adj}
North America	64.124***	24.954***	8.003***	22.959***	25.546***
S. & Cent. America	947.747***	33.346***	2.466**	301.184***	327.422***
Europe & Eurasia	5896.222***	129.535***	35.306***	1164.219***	1327.414***
Middle East	537.177***	33.073***	2.343**	187.607***	219.462***
Africa	1154.217***	34.873***	6.097***	519.751***	608.002***
Asia Pacific	1912.288***	69.645***	4.654***	600.187***	684.318***
Global panel	46,508.850***	301.029***	33.124***	2798.086***	3566.874***

Note: The null hypothesis of the cross-sectional dependence test is no cross-sectional dependence, and the null hypothesis of the slope homogeneity test is slope homogeneity.
*** Indicate significance at the 1% level.
** Indicate significance at the 5% level.

variables for the global panel and various regions are not significant and not consistent with the theoretical expectations outlined in previous studies. This implies that ignoring the cross-sectional dependence and slope homogeneity that may exist within cross countries can create inconsistent estimates. Therefore, the panel CCEMG estimator is chosen as the benchmark estimation method of this study.

According to the panel CCEMG estimations, for the global panel of 128 countries, the coefficients of ln*PS* and ln*GDP* are positive and strongly significant, while the coefficient of ln*REI* is negative and strongly significant. Specifically, in the long run, a 1% increase in ln*PS* and ln*GDP* is associated with a 1.0521% and 0.7032% increase in lnCO_2, respectively, while a 1% increase in ln*REI* leads to a 0.1184% decrease in lnCO_2. These findings are consistent with Shuai et al. (2017) and Danish et al. (2017), who conclude that CO_2 emissions are affected positively by population size and economic growth and negatively by renewable energy consumption. Table 5 also presents the results of the panel CCEMG estimator across the following six regions: North America, S. & Cent. America, Europe & Eurasia, Middle East, Africa, and Asia Pacific. With regard to the variables ln*PS*, ln*GDP*, and ln*REI*, the CCEMG estimator provides similar results for the six regions, indicating that CO_2 emissions are positively and significantly linked to population size and per capita GDP, while increased renewable energy intensity leads to a decline in CO_2 emissions.

In addition, it is worth mentioning that in four regions (i.e., S. & Cent. America, Middle East, Africa, and Asia Pacific) and the global panel, the coefficients of ln*PS* and ln*GDP* are basically similar. Conversely, for North America and Europe & Eurasia, the gap between the coefficients of ln*PS* and ln*GDP* is significant, suggesting that CO_2 is more sensitive to GDP than population growth in these regions.

Table 3
Pesaran CIPS panel unit root analysis.

Variable	Level		1st difference		Order of integration
	Intercept	Intercept & trend	Intercept	Intercept & trend	
North America					
lnCO_2	−0.9196	2.1981	−3.1581***	−4.3005***	I (1)
ln*PS*	2.3278	−0.6384	−3.2401***	−3.7136***	I (1)
ln*GDP*	−0.2847	0.1775	−3.1682***	−2.4817***	I (1)
ln*REI*	0.8983	−0.8103	−7.2519***	−7.1504***	I (1)
S. & Cent. America					
lnCO_2	−0.0959	−0.2196	−11.2157***	−9.7946***	I (1)
ln*PS*	1.3275	−0.1847	−7.5547***	−16.4226***	I (1)
ln*GDP*	1.1208	0.8211	−7.7220***	−5.6804***	I (1)
ln*REI*	2.1979	−0.9974	−11.6027***	−9.4194***	I (1)
Europe & Eurasia					
lnCO_2	−0.2504	−1.4255	−21.7405***	−21.5537***	I (1)
ln*PS*	0.9347	−0.2608	−7.4413***	−9.6351***	I (1)
ln*GDP*	0.7614	−0.7047	−11.2865***	−8.1570***	I (1)
ln*REI*	0.3104	−2.1896**	−13.0476***	−10.3281***	I (1)
Middle East					
lnCO_2	1.4417	−1.2212	−8.5109***	−7.9565***	I (1)
ln*PS*	0.9362	−0.9111	−13.6994***	−22.3560***	I (1)
ln*GDP*	1.9651	−0.6443	−5.8673***	−3.4905***	I (1)
ln*REI*	2.2538	−0.4789	−6.9465***	−6.3345***	I (1)
Africa					
lnCO_2	1.2686	0.6537	−12.0920***	−9.8468***	I (1)
ln*PS*	0.9331	−0.3434	−25.5863***	−32.9208***	I (1)
ln*GDP*	1.4869	−0.4860	−6.8054***	−5.4121***	I (1)
ln*REI*	3.3494	−0.3355	−8.4716***	−6.4010***	I (1)
Asia Pacific					
lnCO_2	0.4298	−0.6013	−9.7219***	−7.8579***	I (1)
ln*PS*	0.9452	−0.8093	−4.6074***	−12.3376***	I (1)
ln*GDP*	1.5829	−1.2615	−8.0531***	−6.3040***	I (1)
ln*REI*	2.0568	0.4275	−8.9462***	−7.0157***	I (1)
Global panel					
lnCO_2	−0.1330	−0.6533	−30.4932***	−27.7695***	I (1)
ln*PS*	−0.2120	−1.4512	−25.4376***	−39.3200***	I (1)
ln*GDP*	−0.7656	−0.6798	−18.8035***	−13.6264***	I (1)
ln*REI*	4.3235	−1.8853**	−23.0820***	−18.6893***	I (1)

Note: Null hypothesis is nonstationarity.
*** Denote statistical significance at the 1% level.
** Denote statistical significance at the 5% level.

4.5. Results of panel causality test

Since a cointegrating relationship is confirmed between CO_2 emission and its determinants, this study further employs the D-H panel causality test to identify the directionality of the causality among the variables. Table 6 presents the empirical results, indicating varied causal links among the variables for the global panel and six subpanel countries. For the global panel, bidirectional causality is found between population size and economic growth and between renewable energy intensity and economic growth. In contrast, unidirectional causality is found to run from population size to CO_2 emissions, economic growth to CO_2 emissions, and renewable energy intensity to CO_2 emissions.

No bidirectional causal relationship is found for North America, while a unidirectional causal relationship is found from population size to CO_2 emissions, economic growth to CO_2 emissions, and renewable energy intensity to CO_2 emissions. Similarly, for S. & Cent. America countries, only a unidirectional causal relationship is identified running from population

Table 4
Westerlund panel cointegration test results.

Region	Test			
	G_τ	G_α	P_τ	P_α
North America	−1.9584**	−2.0745**	−2.6302***	−4.0695***
S. & Cent. America	−6.2012***	−3.0355***	−4.7293***	−3.5363***
Europe & Eurasia	−8.6332***	−4.3838***	−7.7379***	−11.3961***
Middle East	−3.9942***	−3.1773***	−2.8607***	−3.9282***
Africa	−6.9403***	−2.4960***	−5.5765***	−3.0052***
Asia Pacific	−2.7216***	−3.2955***	−3.8040***	−2.1762**
Global panel	−12.8112***	−6.5043***	−11.9700***	−11.8165***

Note: The null hypothesis is no cointegration.
*** Represent the 1% level of significance.
** Represent the 5% level of significance.

Table 5
FMOLS and CCEMG estimation results.

Dependent variable: lnCO_2						
Region	FMOLS estimator			CCEMG estimator		
	ln*PS*	ln*GDP*	ln*REI*	ln*PS*	ln*GDP*	ln*REI*
North America	0.2764	0.2808**	−0.4197***	0.4831***	0.8413***	−0.1603***
	(1.4567)	(2.0828)	(−6.0905)	(29.7975)	(40.5620)	(−24.7392)
S. & Cent. America	1.3763***	0.7480***	0.0800*	0.9640***	0.8362***	−0.3242***
	(13.3444)	(9.9308)	(1.6547)	(173.052)	(40.1906)	(−21.6125)
Europe & Eurasia	0.1181***	0.8149***	−0.1597***	0.1995***	0.8756***	−0.1917***
	(3.8488)	(5.5085)	(−7.4996)	(24.3102)	(228.874)	(−47.3716)
Middle East	0.9319***	0.6305***	−0.0277	1.1137***	0.6820***	−0.1107***
	(14.4628)	(8.7701)	(−0.6456)	(190.229)	(62.2463)	(−21.0361)
Africa	1.1172***	0.8683***	−0.0724	0.9086***	0.8370***	−0.1884***
	(11.6375)	(6.8241)	(−0.9672)	(76.4771)	(49.7871)	(−28.5578)
Asia Pacific	1.0176***	0.6799***	−0.0162	1.1403***	0.7412***	−0.1018***
	(5.1761)	(10.200)	(−0.4825)	(170.772)	(70.0571)	(−16.5310)
Global panel	1.2286***	0.4131***	−0.1547***	1.0521***	0.7032***	−0.1184***
	(26.9120)	(15.8874)	(−9.5126)	(437.053)	(158.296)	(−40.7774)

Note: The values in parentheses represent t-statistics.
*** Denote statistical significance at 1%.
** Denote statistical significance at 5%.
* Denote statistical significance at 10%.

size to CO_2 emissions, economic growth to CO_2 emissions, renewable energy intensity to CO_2 emissions, population size to economic growth, and economic growth to renewable energy intensity. For Europe & Eurasia countries, a bidirectional causal relationship is found between CO_2 emissions and economic growth and population size and economic growth. In addition, a unidirectional causal relationship runs from population size to CO_2 emissions, population size to renewable energy intensity, and renewable energy intensity to CO_2 emissions in Europe & Eurasia countries. Similar to the results of S. & Cent. America countries, a unidirectional causal relationship is identified running from population size to CO_2 emissions, economic growth to CO_2 emissions, renewable energy intensity to CO_2 emissions, population size to economic growth, and economic growth to renewable energy intensity in Middle East countries. For the countries in Africa, no bidirectional causal relationship is found, while a unidirectional causal relationship is found to run from population size to CO_2 emissions, economic growth to CO_2 emissions, renewable energy intensity to CO_2 emissions, economic growth to population size, and economic growth to renewable energy intensity. For Asia Pacific, this study finds a unidirectional causal relationship running from population size to CO_2 emissions, economic growth to CO_2 emissions, renewable energy intensity to CO_2 emissions, economic growth to population size, and economic growth to renewable energy intensity. Concerning the relationship between economic growth and renewable energy intensity, a bidirectional causal relationship is found in Asia Pacific countries.

5. Further discussion

5.1. Robustness analysis

As the first step in the discussion part, the estimates obtained from the CCEMG estimator are further tested for robustness by employing the panel AMG estimator. The results of the CCEMG and AMG estimators are presented in Table 7. For the global panel and six subpanel countries, the long-run estimates of the AMG estimator are consistent with the CCEMG estimates as the signs of all the variables are similar, indicating that the results acquired from the CCEMG estimator are robust. Furthermore, the differences in root mean square error (RMSE) value are chosen to test for the robustness of estimation results by referring to the work of Dong et al. (2017a). As shown in Table 7, expect for the countries in Africa, the RMSE values produced by the CCEMG estimator are slightly lower than those of the AMG estimator and, therefore, the parameter estimates from the CCEMG estimator are preferred.

5.2. Spatial distributions of economic growth, proportion of renewable energy, and coefficient of renewable energy intensity

Fig. 3 illustrates the spatial distributions of economic growth, proportion of renewable energy, and coefficient of renewable energy intensity for the six regions, implying that the occurrence of the significantly

Table 6
Results of D-H panel causality test.

No.	Null hypothesis (H_0)	North America	S. & Cent. America	Europe & Eurasia	Middle East	Africa	Asia Pacific	Global panel
1	$CO_2 \neq PS$	0.6493	0.3590	0.7198	0.5364	0.1614	1.9874	0.0190
2	$PS \neq CO_2$	3.5955**	8.1037***	39.1344***	4.8712***	7.0939***	10.4475***	37.4411***
3	$CO_2 \neq GDP$	1.0051	2.2888	2.9051*	1.3308	0.9598	0.8634	1.2676
4	$GDP \neq CO_2$	6.4774***	10.3805***	2.6455*	2.4517*	13.9323***	11.9065***	74.9705***
5	$CO_2 \neq REI$	0.7491	0.7091	0.5498	1.4077	1.0455	0.1090	0.5408***
6	$REI \neq CO_2$	16.4553***	3.4835**	3.1686**	3.9678**	5.2001***	5.4880***	4.9305***
7	$PS \neq GDP$	1.9475	4.1547**	18.9985***	6.5792***	0.1455	1.0060	26.2929***
8	$GDP \neq PS$	1.4178	0.4600	12.0606***	0.7861	3.3648**	9.9068***	17.6084***
9	$PS \neq REI$	0.2678	0.0496	16.8573***	0.5172	0.0462	2.2551	0.6707
10	$REI \neq PS$	0.3750	0.2464	0.0691	0.4958	1.0067	2.0895	1.0410
11	$GDP \neq REI$	2.3640	5.2081***	1.1902	6.4283***	5.6214***	21.6032***	35.1224***
12	$REI \neq GDP$	1.9220	0.1269	0.8304	0.7331	0.9737	7.9815***	2.8728*

Notes: The values denote the Wald statistics, and $A \neq B$ indicates that A does not cause B.
*** Denote the 1% level of significance.
** Denote the 5% level of significance.
* Denote the 10% level of significance.

Table 7
Results of robustness analysis.

Dependent variable: $\ln CO_2$							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CCEMG estimator							
ln*PS*	0.4831***	0.9640***	0.1995***	1.1137***	0.9086***	1.1403***	1.0521***
	(29.7975)	(173.052)	(24.3102)	(190.229)	(76.4771)	(170.772)	(437.053)
ln*GDP*	0.8413***	0.8362***	0.8756***	0.6820***	0.8370***	0.7412***	0.7032***
	(40.5620)	(40.1906)	(228.874)	(62.2463)	(49.7871)	(70.0571)	(158.296)
ln*REI*	−0.8603***	−0.3242***	−0.1917***	−0.1107***	−0.1884***	−0.1018***	−0.1184***
	(−24.7392)	(−21.6125)	(−47.3716)	(−21.0361)	(−28.5578)	(−16.5310)	(−40.7774)
RMSE	0.0282	0.0398	0.0196	0.0277	0.0299	0.0312	0.0133
AMG estimator							
ln*PS*	0.8626***	0.8792***	0.3031***	1.0809***	0.9418***	1.0472***	1.0436***
	(12.2674)	(70.1927)	(19.3445)	(112.9975)	(46.8154)	(50.3479)	(146.5262)
ln*GDP*	0.8755***	0.0051***	0.9969***	0.7245***	0.8640***	0.5011***	0.6333***
	(51.6815)	(8.1631)	(94.0607)	(41.1112)	(22.6290)	(16.1816)	(57.3056)
ln*REI*	−0.2820***	−0.8532***	−0.1284***	−0.0954***	−0.1860***	−0.2787***	−0.2219***
	(−2.6601)	(−28.5505)	(−9.5379)	(−11.0173)	(−9.4857)	(−12.0912)	(−27.4236)
RMSE	0.0786	0.0893	0.0883	0.0614	0.0108	0.0830	0.0430

Note: The values in parentheses represent t-statistics; and (1)–(7) indicate North America, S. & Cent. America, Europe & Eurasia, Middle East, Africa, Asia Pacific, and Global panel, respectively.
*** Denotes statistical significance at 1% level.

negative effect of renewable energy intensity on CO_2 emissions is independent of the region-specific economic growth level and geographic location. This means that the negative and statistically significant coefficient of renewable energy intensity would arise in any region regardless of whether the economic growth level of the selected region is low or high. Specifically, with respect to the annual average per capita GDP in 2014 (see Fig. 3), although North America (approximately $40,006.4) and Africa (approximately $1801.8) are the richest and poorest region among the sample regions, respectively, their CO_2 emissions are negatively and significantly linked with renewable energy intensity. This finding coincides with existing studies, such as Bilgili et al. (2016), which confirm that the significantly negative effect of renewable consumption on CO_2 emissions does not depend on the country-specific income level.

Although increasing renewable energy intensity can negatively and significantly affect CO_2 emissions in all of the six regions, as shown in Table 5, the coefficients of renewable energy intensity in S. & Cent. America and Europe & Eurasia are considerably higher than the levels seen in other regions. Meanwhile, for S. & Cent. America and Europe & Eurasia, the proportion of renewable energy consumption in the primary energy mix (more than 10%; see Fig. 3) is considerably higher than the levels seen in other regions. More specifically, renewable energy in S. & Cent. America and Europe & Eurasia has increased rapidly, providing 26.1% and 12.1% of their total energy needs in 2014, respectively. These findings imply that the impact strength of renewable energy intensity on CO_2 emissions can be affected by energy consumption structure (i.e., the share of renewable energy in total energy consumption), which is consistent with Bélaïd and Youssef (2017) and Chiu and Chang

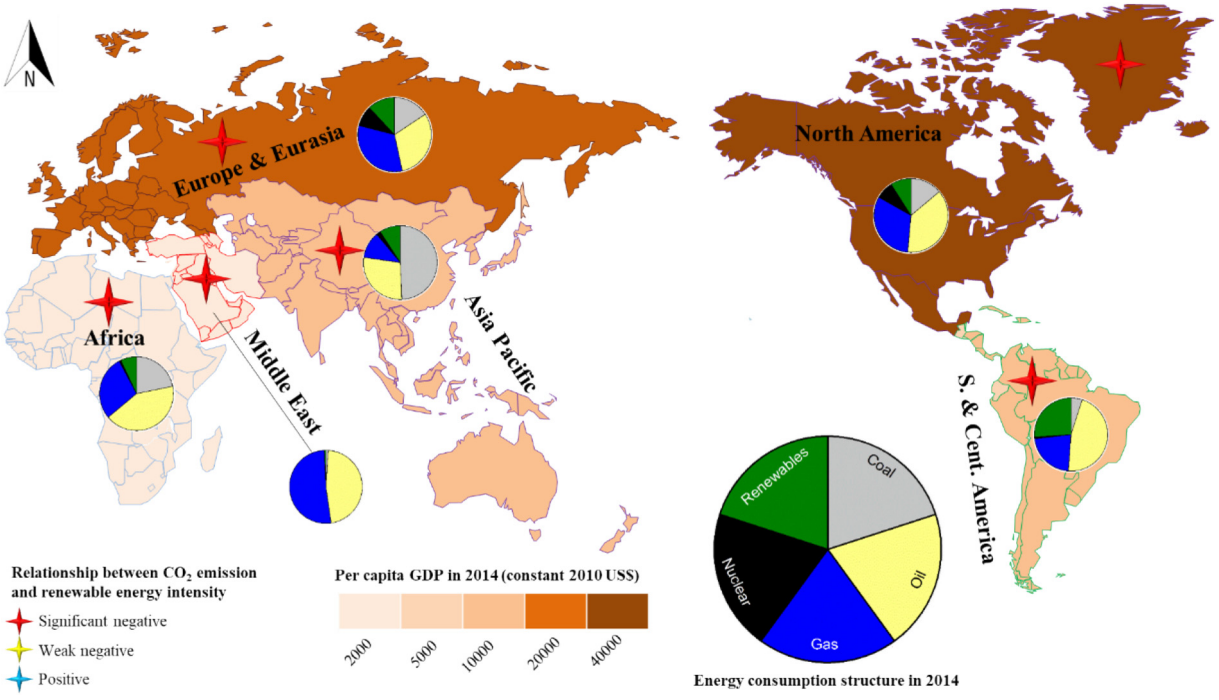

Fig. 3. Spatial distributions of economic growth and the coefficient and the proportion of renewable energy.
(*Data source*: BP, 2017; World Bank, 2017.)

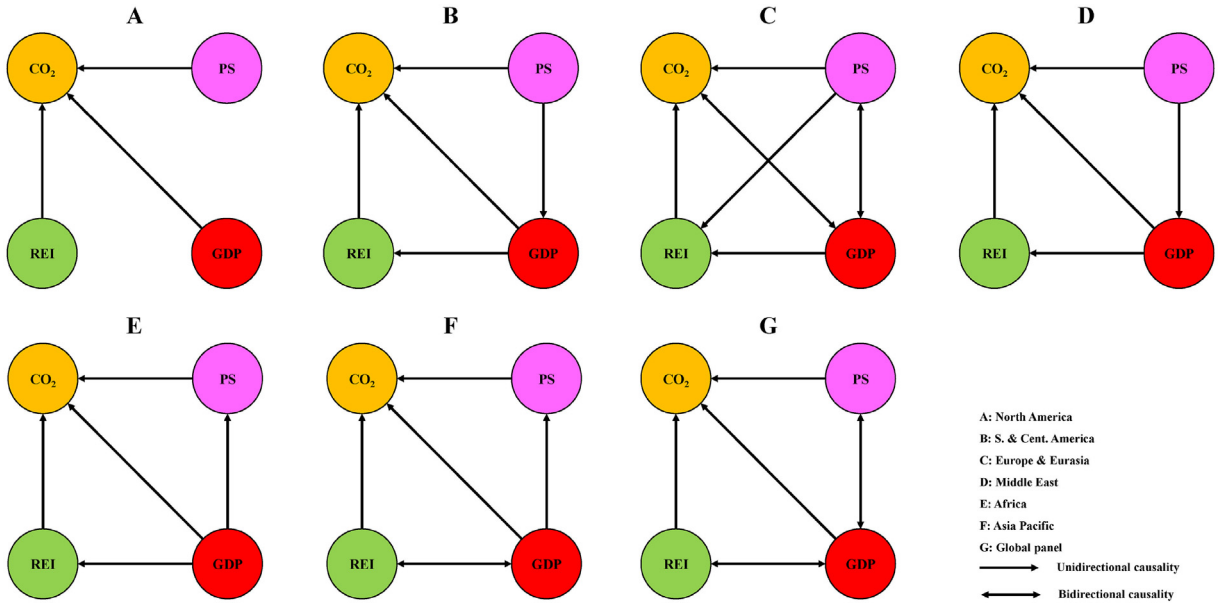

Fig. 4. Causality relationships flow.

(2009), who point out that renewable energy makes a noteworthy contribution to mitigating CO_2 emissions only when its consumption exceeds 8.4% of total energy need.

5.3. What can we learn from the causality relationships across regions?

Based on the results of Table 6, Fig. 4 summarizes the results of causality movements. From this figure, we can see that the directionality of causality among the variables across different regions is determined by a variety of factors (Chou, 2013). Meanwhile, the mixed results are particularly useful for each region's policymakers in developing specific policies for tackling CO_2 emissions. For example, the unidirectional Granger causal relationship from renewable energy intensity to CO_2 emissions infers that, along with the rapidly increasing demand for renewable energy, the global CO_2 emissions can be effectively mitigated in the future. This finding is in line with the prior work of Bilgili et al. (2016). Furthermore, the unidirectional causality running from economic growth to CO_2 emissions supports the argument that CO_2 emissions may not be a limiting driver of economic growth. This outcome supports the previous work of Ali et al. (2017) for Malaysia.

6. Conclusion and policy implications

To investigate empirically the dynamic linkages among CO_2 emissions, economic and population growth, and renewable energy while accounting for unobserved time invariant differences across various regions, an unbalanced panel dataset of 128 countries covering 1990–2014 is utilized in this study. Considering the cross-sectional dependence and slope homogeneity observed in the panel, a causality framework covering panel unit root, cointegration, estimation, and causality tests allowing for cross-sectional dependence and slope homogeneity is employed in this study.

The main findings of this study are as follows. First, the results of cross-sectional dependence tests confirm strong interdependencies within and across countries due to the increasing economic integration. Second, at both the global and regional level, population size and economic growth positively and significantly influence CO_2 emission levels. Third, at the global level, increased renewable energy intensity can lead to a decline in CO_2 emissions. More specifically, a 1% increase in renewable energy intensity leads to a 0.1184% decrease in CO_2 emissions. At the regional level, although increased renewable energy intensity can lead to CO_2 emissions reduction for all of the six regions, the coefficients of renewable energy intensity in S. & Cent. America and Europe & Eurasia are considerably higher than the levels seen in other regions, which can be affected by energy consumption structure (i.e., the share of renewable energy in total energy consumption). Fourth, our results suggest that the occurrence of the significantly negative effect of renewable energy on CO_2 emissions is independent of the region-specific economic growth level and geographic location. In other words, the negative and statistically significant coefficient of renewable energy would arise in any region regardless of whether the economic growth level of the selected region is low or high.

The policy implications of the above results are as follows: First, given that significant cross-sectional dependence tends to exist within and across countries, cooperation on the international and/or regional level is needed to halt global warming. Second, for the global panel, economic growth is highly emission intensive, and economic growth often means rising energy consumption and increasing CO_2 emissions; thus, promoting the economic transition to renewables plays a crucial role in mitigating the environmental pressure resulting from economic growth. In addition, population size is also an important factor contributing to CO_2 emissions and requires immediate policy response at the global level. Third, our results suggest that the occurrence of the significantly negative effect of renewable energy intensity on CO_2 emissions is independent of the region-specific economic growth level and geographic location, but the impact strength of renewable energy intensity on CO_2 emissions may be affected by the energy consumption structure (i.e., share of renewable energy in total energy consumption). From this perspective, to effectively control CO_2 emissions, every region, regardless of whether it is a low-income or high-income region, should spend its effort to increase its share of renewable energy in the total energy needs and adopt effective policies to discourage the use of non-renewable energy.

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Appendix A

Table A1
Summary of selected previous studies on the emission- growth-renewables nexus (2010–2017).
(Source: Compiled by the authors.)

Author	Study area	Period	Variable	Methodology	Causality	CD-SH
Apergis et al. (2010)	19 countries	1984–2007	CO_2, NU, RE, Y	ECM Granger causality	RE → CO_2	×
Menyah and Wolde-Rufael (2010)	US	1960–2007	CO_2, NU, RE, Y	VAR model	CO_2 → RE	×
Menegaki (2011)	Europe	1997–2007	CO_2, EM, RE, EC, Y	Panel ECM	Neutrality between RE and Y	×
Apergis and Payne (2014)	7 Central American countries	1980–2010	CO_2, RE, CP, OP, Y	FMOLS, Regime-wise Granger causality	RE ↔ Y; RE ↔ CO_2	×
Azlina et al. (2014)	Malaysia	1975–2011	CO_2, RE, EC, Y, Y^2	VECM Granger causality	Y → RE	×
Lin and Moubarak (2014)	China	1977–2011	CO_2, RE, L, Y	VECM Granger causality	RE ↔ Y and CO_2 → RE (LR)	×
Sebri and Ben-Salha (2014)	BRICS countries	1971–2010	CO_2, RE, TO, Y	ARDL	RE ↔ Y; CO_2 → RE	×
Shafiei and Salim (2014)	OECD countries	1980–2011	CO_2, RE, NRE, Y, Y^2	GMM method	RE → CO_2	√
Zeb et al. (2014)	SAARC countries	1975–2010	CO_2, NRD, POV, Y	VECM Granger causality	RE → Y for India, neutrality for other countries; RE → CO_2	×
Jaforullah and King (2015)	USA	1965–2012	CO_2, NU, RE, EP, Y	VECM Granger causality	RE → CO_2	×
Özbuğday and Erbas (2015)	36 countries	1971–2009	CO_2, POP, EFF, MSG, RE	Heterogeneous panel analysis	RE → CO_2	√
Bento and Moutinho (2016)	Italy	1960–2011	CO_2, RE, NRE, TO, Y, Y^2	Toda-Yamamoto causality	Y → RE; NER → RE	×
Bilgili et al. (2016)	17 OECD countries	1977–2010	CO_2, RE, Y, Y^2	FMOLS, DOLS	RE → CO_2	×
Dogan and Seker (2016)	EU-15 countries	1980–2012	CO_2, RE, NRE, Y, Y^2	Dumitrescu–Hurlin panel Granger causality	RE ↔ CO_2; No causality between RE and Y	×
Irandoust (2016)	4 Nordic countries	1975–2012	CO_2, RE, R&D, Y	VAR	RE → CO_2 for Denmark and Finland, RE ↔ CO_2 for Sweden and Norway; Y → RE	×
Jebli et al. (2016)	25 OECD countries	1980–2010	CO_2, RE, NRE, TO, Y, Y^2	VECM Granger causality	RE ↔ CO_2, RE ↔ Y (LR);	×
Moutinho and Robaina (2016)	20 OECD countries	1991–2010	CO_2, RE, Y, Y^2	Panel Granger causality	RE ↔ Y	×
Saidi and Mbarek (2016)	9 developed countries	1990–2012	CO_2, NU, RE, Y	VECM Granger causality	RE → CO_2, RE ↔ Y (LR); RE → Y (SR)	×
Sugiawan and Managi (2016)	Indonesia	1971–2010	CO_2, RE, Y, Y^2	ARDL	RE → CO_2, Y → CO_2,	×
Bélaïd and Youssef (2017)	Algeria	1980–2012	CO_2, RE, NRE, Y, Y^2	VECM Granger causality	RE → CO_2	×
Bhattacharya et al. (2017)	85 economies	1991–2012	CO_2, RE, NRE, IQ, Y	GMM; FMOLS	RE → CO_2; RE → Y	×
Danish et al. (2017)	Pakistan	1970–2012	CO_2, RE, NRE, Y, Y^2	VECM Granger causality	RE ↔ CO_2 (LR, SR)	×
Dong et al. (2017a)	BRICS countries	1985–2016	CO_2, RE, NG, Y, Y^2	VECM Granger causality	RE ↔ CO_2 (LR)	√
Ito (2017)	42 countries	2002–2011	CO_2, FECs, RE, Y	GMM, PMG	RE → CO_2 (LR)	√
Li and Su (2017)	USA	1990–2015	CO_2, RE, N, Y	VAR	RE → CO_2	×
Mehdi and Slim (2017)	North Africa countries	1980–2011	CO_2, RE, AGR, Y	VECM Granger causality	RE → CO_2 (LR)	×
Paramatia et al. (2017)	G20 countries	1991–2012	CO_2, RE, NRE, POP, Y	Panel Granger causality	RE → CO_2	×
Zoundi (2017)	25 African countries	1980–2012	CO_2, RE, Y, Y^2	FMOLS, DOLS	RE → CO_2 (LR)	×

Notes: 1) Variables: RE is renewable energy; L is labor; Y is gross domestic product (GDP)/per capita; Y^2 is per capita GDP (squared); NU is nuclear energy; CO_2 is carbon emissions; EC is energy consumption; EM is Employment; NRE is non-renewable energy; TO is trade openness; CP is coal prices; OP is oil prices; NRD is natural resource depletion; POV is poverty; EP is energy prices; POP is population; EFF is energy efficiency; MSG is manufacturing share of GDP; R&D is research and development; IQ is institutional quality; AGR is per capita agricultural value added; FECs are various fossil fuels; NG is natural gas; and ***2) Methods:*** VECM is vector error correction model; ECM is error correction method; VAR is vector autoregressive model; OLS is ordinary least squares; FMOLS is fully modified OLS; ARDL is autoregressive distributed lag model; DOLS is dynamic OLS; and GMM is generalized method of moments. **3)** CD-SH indicates that whether this work has considered the cross-sectional dependence and slope homogeneity, √ is YES, while × is NO.

Table A2
Description of the variables in the study.

Variable	Definition	Supporting reference	Data source
lnCO_2	CO_2 emissions (metric tons)	Wang et al. (2013); Yue et al. (2013); Shuai et al. (2017)	World Bank (2017)
ln*PS*	Total population size (number)(	Poumanyvong and Kaneko (2010); Lv (2017); Wang et al. (2017b))	World Bank (2017)
ln*GDP*	Per capita GDP (constant 2010 US$)(	Shuai et al. (2017); Wang et al. (2017a); Zhou et al. (2008)	World Bank (2017)
ln*REI*	Renewable energy use per capita GDP (kg of oil equivalent per constant 2010 US$)(	López-Menéndez et al (2014); Yang (2014)	World Bank (2017)

Table A3
List of countries (economies) based on location.

Subpanel	Countries (economies)
North America (3 economies)	Canada, Mexico, United States
S. & Cent. America (22 economies)	Argentina, Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Nicaragua, Panama, Paraguay, Peru, St. Kitts and Nevis, Trinidad and Tobago, Uruguay, Venezuela
Europe & Eurasia (40 economies)	Albania, Armenia, Austria, Azerbaijan, Belarus, Belgium, Brazil, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom
Middle East (14 economies)	Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Saudi Arabia, Syrian Arab Republic, Tajikistan, Turkey, United Arab Emirates, Yemen
Africa (25 economies)	Algeria, Angola, Benin, Botswana, Cameroon, Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Ethiopia, Gabon, Ghana, Kenya, Mauritius, Morocco, Mozambique, Namibia, Nigeria, Senegal, Sudan, Suriname, Tanzania, Togo, Tunisia, Zambia, Zimbabwe
Asia Pacific (24 economies)	Australia, Bangladesh, Cambodia, China, Hong Kong SAR, India, Indonesia, Japan, Kazakhstan, Korea Rep., Kyrgyz Republic, Malaysia, Mongolia, Myanmar, Nepal, New Zealand, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Turkmenistan, Uzbekistan, Vietnam

Note: Country groupings are made purely for statistical purposes and are not intended to imply any judgment about political or economic standings.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.08.017.

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